Human Physiological Behavior Understanding and Parameter Tracking Based on Complex Network Theory

Han Li[1,2](✉) and Peng Du[1,2]

[1] School of Electronic and Information Engineering, Liaoning University of Technology, Jinzhou 121000, China
lihan562323@yeah.net

[2] LiaoNing Wish Information Technology Co., Ltd., Jinzhou 121000, China

Abstract. In order to accurately track, analyze and understand human physiological behavior parameters, a method of human physiological behavior understanding and parameter tracking based on complex network theory is established. By defining the complex network theory, the statistical properties of complex networks are studied, and the central index of correlation degree of nodes is combined to analyze the structural characteristics of complex networks. On this basis, the human skeleton modeling conditions are set up, and the final result of parameter tracking behavior recognition is obtained according to the multi-scale feature extraction process. Experimental results show that the parameter tracking method based on complex network theory can accurately record the changes of human physiological behavior compared with traditional multi-scale human physiological behavior analysis method.

Keywords: Complex network · Human physiological behavior · Parameter tracking · Multi-scale feature

1 Introduction

With rapid economic development, increasingly fierce social competition, people's lives is getting faster and faster, the pressure of work and live increases. Common symptoms such as insufficient sleep, obesity, and immunity disorders threaten human health. With the development of science and technology, medical aids play an increasingly important role. Physiological parameters are the most basic life indicators of the human body, and medical workers can timely understand the disease condition through monitoring the human life indicators and parameters. The collection of physiological parameters and human wireless monitoring belong to biological telemetry. Through the method of radio magnetic signal transmission, the continuous collection of various important physiological parameters and intelligent monitoring is a part of the modern medical system. At present, technologies such as wireless communication and mobile Internet have been applied to small and medium-sized mobile communication devices, while the

S. Liu and X. Ma (Eds.): ADHIP 2021, LNICST 416, pp. 3–14, 2022.
https://doi.org/10.1007/978-3-030-94551-0_1

application of wireless communication and Internet technologies to medical equipment is still in its infancy. At present, there are some defects in the telemedicine monitoring system on the market, such as the monitoring results are not accurate enough, complex operation, and users can not get their own health status anytime and anywhere. To solve the above problems, this paper designs the human physiological behavior understanding and parameter tracking system based on complex network theory. Complex network theory focuses on the relationship between the complexity of the network structure and the network function, providing a powerful tool to reveal the nonlinear dynamic behavior of complex systems. The physiological behavior of the human body is very complex, dynamic and changeable, without real-time monitoring and analysis with a simple linear tracking system, so the complex network theory must be used. This paper presents a system of this theoretical design that can make users monitor their own physiological parameters in real time, and the data is more accurate, can better meet the health needs of people, so that everyone can understand their own health status at any time, prevent and monitor the occurrence of disease in advance [1].

Complex network is a kind of network with some or all properties of self-organization, self-similarity, attractor, small world and scale-free. Characteristics: Small world, cluster is the concept of degree of agglomeration, degree distribution of power law. Complex networks are, in short, networks of high complexity. Its complexity is mainly shown in the following aspects:

1) The complexity of the structure is mainly manifested in the huge number of nodes. network structure presents a variety of different characteristics.
2) Network evolution is mainly manifested in the emergence and disappearance of nodes or connections. For example, world-wide network, web pages or links may appear or break at any time, resulting in constant changes in the network structure.
3) Connection diversity: there are differences in connection weights among nodes, and there may be directionality.
4) Dynamical complexity: the node set may be a nonlinear dynamical system, for example, the node state changes complicated with time.
5) Node diversity: A node in a complex network can represent anything. For example, a node in a complex network composed of human relationships can represent an individual, and a node in a complex network composed of the World Wide Web can represent a different web page.
6) Multiple complexity fusion: that is, the above multiple complexities interact with each other, leading to more unpredictable results. For example, to design a power supply network, we need to consider the evolution process of the network, which determines the topology of the network. When two nodes transmit energy frequently, the connection weights between them will be increased, and the network performance will be improved gradually through continuous learning and memory.

2 Analysis of Structural Characteristics of Complex Network Theory

2.1 Overview of Complex Network Theory

Complex network is a large scale network with complex topological structure and complex dynamic behavior. It is a graph composed of a large number of nodes connected by edges, which is highly abstract. The complex network theory focuses on the relationship between the complexity of network structure and the function of network, which provides a powerful tool for revealing the nonlinear dynamic behavior of complex systems. The development of the complex network stems from the famous eighteenth-century Swiss mathematician Leonhard Euler's Seven Bridges at Cornisberg. That is, how to start from any of the four continents and cross each bridge exactly once when you return to the starting point. Euler uses abstraction analysis to turn the problem into a graphical problem: each land is replaced by a point, and each bridge is replaced by a line connecting the corresponding two points. So you get a simple "map".

Euler's scientific explanation of the seven-bridge problem initiated the study of graph theory, which is in line with the study of complex networks in some way. When people use stochastic networks to describe real networks, it is found that most of the real complex networks are not completely random in structure, which arouses the interest of many scholars. At the end of the nineteenth century, the discovery of the small-world and scale-free characteristics of complex networks led to a historic change in the scientific exploration of complex networks, which led to an upsurge of research on complex networks theory in many disciplines, marking the arrival of the era of "new science of networks" and the birth of a new interdisciplinary discipline of network science and engineering.

With the rapid development of complex network theory, many structural parameters in the sense of network statistics have been proposed by scholars. These parameters can be used to describe the importance of nodes or edges in complex networks from different perspectives. For example, the degree centrality index is the most basic evaluation method of node importance, which reflects the direct influence of nodes in their neighborhood. However, key nodes cannot be accurately identified because the indicator does not take into account the global importance of nodes [2]. In contrast, the central index can evaluate the importance of nodes in the whole network from a global point of view, which shows the control ability of nodes or edges in providing the shortest available routing. These methods use a single centrality index to measure the importance of nodes from different angles, but it is difficult to evaluate the importance of nodes accurately because of the large scale and complexity of real networks and the diversity of different topologies.

2.2 Statistical Properties of Complex Networks

For a complex network with small-world characteristics, it has a large clustering coefficient and a small average path length. Here, "a large clustering coefficient" is relative to a regular network, while "a small average path length" is relative to a random network. Clustering coefficients and average path length are proposed to characterize the topological characteristics of complex networks [3]. In addition, many other concepts of statistical properties have been proposed, such as degree and its distribution, medium number, efficiency, etc.

The degree value l_i of a node refers to the number of connected edges between node s_i and adjacent nodes (where i represents the actual statistical measurement coefficient of the complex network). Node degree is one of the most simple and important concepts in the statistical characteristics of complex networks. It is used to reflect the richness of nodes in the network and the direct influence of nodes in the network. According to the definition of node degree, we can get the average degree of the network, that is, the average value of all node degrees in the network, which is represented by l. Furthermore, the degree centrality index of node s_i refers to the ratio of the number of nodes directly associated with node s_i to the maximum number of nodes possibly associated with node 1.

$$DC(i) = \frac{l_i}{i - 1} \tag{1}$$

Among them, $DC(i)$ reflects the proportion of the number of nodes with degree value of l_i in the total number of nodes in the network. The degree distribution of different network topologies is shown in Table 1.

Table 1. Comparison of characteristics of different network types

	Degree distribution	Feature path length	Agglomeration coefficient
Rule network	δ distribution	Large	Large
Random network	Poisson distribution	Small	Large
Small world network	Exponential distribution	Small	Large
Ba scale free network	Power law distribution	Small	Small
Actual network	Approximate power law distribution	Small	Large

Because of the individual differences in network connection and network function among the nodes that make up the basic unit of complex network, the strategies of node protection should be different. The structural attributes of complex networks are described by the central index of the statistics which characterizes the topological structure, while the functional attributes are described by the characteristic attributes which have specific meanings and functions according to the operation mode of networks. When a system is abstracted into a complex network, the importance of a node must be determined by its structural and functional attributes in the network. Accurately identifying the importance of complex network nodes is not only the premise for network managers to defend the network security, but also the effective way for attackers to lock the attack target.

The basic idea of multi-attribute node importance recognition algorithm based on information entropy is to take each node in complex network as a decision scheme, take the selected centrality index as the attribute of each decision scheme, get the direct value of each attribute and calculate the weight of each attribute according to information entropy, and the node importance is the weighted sum of the attribute values of each scheme [4]. For a decision attribute, the smaller its direct value, the more uneven the distribution of the value of the attribute, the corresponding greater its weight value; otherwise, the smaller the weight value. In particular, when the equal probability of the value of an attribute appears, the distribution of the value of the attribute is the most uniform, the direct value is the largest, and the weight of the attribute for evaluating the node importance is the least, that is, the attribute has the least impact on the evaluation results.

2.3 Node Correlation Degree Central Index

In 1865, the German physicist Rudolf Clausius first proposed the concept of the entropy and applied it to the study of human physiology to show the uniformity of the distribution of any energy in space. Then, Boltzmann and Planck gave the microscopic statistical formula of the entropy, which is used to measure the disorder degree of the system and lay the foundation for the application of the entropy in multidisciplinary. In 1948, Shannon, the American mathematician and founder of information theory, first introduced the concept of entropy into information theory when he solved the problem of quantifying information in communication. Information entropy is a concept used in information theory to measure the degree of uniformity and orderliness of information.

For a discrete random signal source $X = \{x_1, x_2, \cdots, x_n\}$ and its probability distribution, the definition of information entropy $P(X) = \{P(x_1), P(x_2), \cdots, P(x_n)\}$ is as follows

$$H = \frac{-\sum_{i=1}^{m} P(x_i) \ln P(x_i)}{DC(i)} \tag{2}$$

Among them, m represents the definition coefficient of correlation degree, and $P(x_i)$ represents the network microscopic statistics of signal source x_i, i has the same meaning as formula (1).

In complex networks, there are complex interdependencies among nodes. How to describe the strength of the interdependencies is closely related to the accuracy of node importance identification. Based on this, a centrality index of association degree is proposed in this section. This index is mainly considered from the following three aspects:

First, the correlation range of importance between nodes. It is generally believed that the most direct form of correlation between nodes lies in the adjacent nodes. In practice, does the interaction between nodes only exist between adjacent nodes? If the correlation strength between non adjacent nodes is much lower than that between adjacent nodes, the correlation between non adjacent nodes can be ignored. However, if the degree of correlation between non adjacent nodes is significantly higher than that of adjacent nodes, then the correlation between non adjacent nodes can not be ignored. The relationship between nodes can be considered as interdependence, and can be described by the contribution of node importance. In addition, due to the inherent importance of the node itself, the important contribution of the node is bound to be uneven.

3 Human Physiological Behavior Understanding and Parameter Tracking Method

3.1 Human Skeleton Modeling

When the clothing of human body is close to the background, the detected human body will appear holes, and due to the interference of noise and shadow, the detected foreground image often has isolated points. In order to eliminate these adverse effects, we use morphological methods to deal with noise and holes, so as to get a better binary image, as shown in Fig. 2.

First, all the pixels in the image are added with the corresponding tag array, and the array is initialized to 0; then, a point on the background area is used as the seed point to grow the region, and all the pixels scanned in the growth process are marked as 1; finally, through the operation of step 2, all the points marked as 1 are the background points, and the points marked as 0 are the detected objects and holes. If the gray value of all the pixels marked as 0 is set as the foreground color, the hole can be filled, and a better binary image effect can be obtained. Although the principle of background subtraction is simple, the construction and update method of background image is very important, because it directly affects the adaptability of background model to scene change and foreground target granularity [5, 6]. There are many methods for background update, such as selective update and blind update.

In view of the fact that expansion and corrosion are not a pair of reciprocal operations, we can do some special processing on the image through the operation of expansion first and then corrosion. After several times of expansion operation, the tiny fracture of binary image can be connected, and then several times of corrosion operation can be carried out, so that the redundant information generated by the expansion of the object periphery can be eliminated. In this way, not only the image information is complete, but also the noise is not introduced (Fig. 1).

Fig. 1. Human skeleton modeling form

In the field of complex network, the preprocessing of human physiological behavior image usually includes the main steps of foreground detection, denoising and filling holes. If the human body is modeled to extract features, the known 2D modeling method is a star skeleton model based on the distance from the center point to the contour point, or a 2D model based on the mapping of human body structure to the skeleton [7]. Firstly, the gray image is denoised by Gaussian filter, then the moving object is detected by background subtraction method, and the moving object image is post-processed, such as denoising and filling holes. The skeleton is extracted by morphological method, and then the key points of the skeleton, including limb end point, bifurcation point and upper limb inflexion point, are obtained by using chain code and curvature.

3.2 Multi-Scale Feature Extraction

For different tracking occasions and understanding purposes, human physiological behavior maintains different motion characteristics on the rough layer, the middle layer and the fine layer of the complex network. In the middle layer, people's motion-related behaviors reflect people's actions at every moment, such as bending down, stretching out hands, etc., and the features are usually represented by the outline of a human being or binary silhouette. In the details layer, the movement of a person's limb needs to be accurately expressed, the state changes quickly, and the features are usually represented by point coordinates. The features of different levels reflect the motion on different scales. We extract the features from different scales, which are called multi-scale features. These three scales are referred to as large scale, mesoscale and small scale [8]. Motion details on different scales play different roles in behavior recognition. How to combine them properly is of great significance to behavior recognition.

On a large scale, the speed of human action has the characteristics of this scale.

(1) Get the outline of the human body's binary silhouette;
(2) Finding the center point of the outline;

The speed of human motion is determined from the distance and time of the centroid movement in the continuous frame image.

If there is an obvious reference object in the background, the distance between the reference object and the human being is another large-scale feature; if there is no reference object, only the speed is selected as the feature, so the large-scale feature in the complex network environment only selects the tracking speed of human physiological behavior.

On the mesoscale, the body contour is used for feature extraction. The features of this scale include three levels:

(1) Scanning contours from top to bottom, taking the width of each line of contours as the first mesoscale feature, which can reflect the amplitude of upper and lower limb movement;
(2) The second mesoscale feature is the number of intersections between the line and the contour. The position of limb can be determined by the number of intersections. If the number of intersections is more, the position of limb can be determined.

(3) The cycle of upper limb swings is taken as a third characteristic dimension, as it reflects the speed of upper limb movement.

On the small scale, we use the position of human limbs, head and upper limb inflection point to depict human motion, i. e. extract the coordinated position of the human head, two hands and two feet, bifurcation point and upper limb inflection point as the small scale feature, altogether 8 points and 16 dimensional feature. Firstly, the background is extracted from the motion sequence, and then the foreground region is extracted by background subtraction to obtain binary silhouette. Many behavioral recognition algorithms based on multiple viewpoints choose binary silhouette as feature input. Features of different scales describe different behavioral characteristics, which can combine features of different scales together to express the behavioral performance more completely. A simplified 2-D model of human body is established by calculating the local maximum distance from body mass center to limbs and head, and the human body action sequence is represented as a continuous 2-D star skeleton, which is matched with the feature template for behavior recognition [9]. The location of these key parts is of great significance to the analysis of more subtle and subtle movements in human behavior. Based on the human skeleton model obtained in the previous chapter, the position of head, limb, bifurcation point and inflection point can be obtained accurately, which can more accurately depict the state of human in motion.

3.3 Parameter Tracking Behavior Recognition

Clustering is a collection of data objects. In the same class, data objects are similar, but objects between different classes are not similar. Cluster analysis is the grouping of data sets into several clusters. Clustering is an unsupervised classification, that is, there is no predefined class. Typical applications of clustering are: as an independent tool to look at data distribution; as a preprocessing step for other algorithms. Tracking behavior is a multilinear mapping over a set of vector spaces. Multilinear analysis is an extension of traditional linear methods such as PCA or matrix singular value decomposition. Tracking behavior is a generalization of the concepts of vector and matrix. Because the tracking behavior has such good characteristics, it can play a very good role in pattern recognition under the influence of multiple factors. Each factor is placed on a dimension of a high dimensional tensor, so that each factor can be decomposed independently on the corresponding dimension, and the components decomposed independently are controlled by a unified kernel tensor.

Feature extraction is to map the data set to a space, and take the basis of the space as a variable to model from the data set; Behavior classification classifies the behavior sequence into a concrete class. In the research of parameter tracking behavior recognition, first of all, the current feature extraction methods are introduced, mainly based on non-model and model-based methods. The non-model based methods are mainly based on contour or binary silhouette as feature, and the method of extracting the optical flow vector from the optical flow field to reflect the movement of the object by the change of the optical flow vector, which is mainly applied to the detection and tracking of the moving object, or combined with the time characteristic of the movement, use the moving historical image as feature to carry out template matching to identify the object.

Model-based methods mainly include two-dimensional models and three-dimensional models [10].

Under the support of complex network theory, several common behavioral recognition methods, such as template-matching method, probabilistic network method, hidden Markov model and dynamic Bayesian network are the most commonly used models. Other methods such as the method based on clustering analysis, neural network -based methods. Recently, the behavior recognition method based on tensor quantum space analysis has been paid more attention to, and it has been applied to the field of behavior recognition from the initial face recognition.

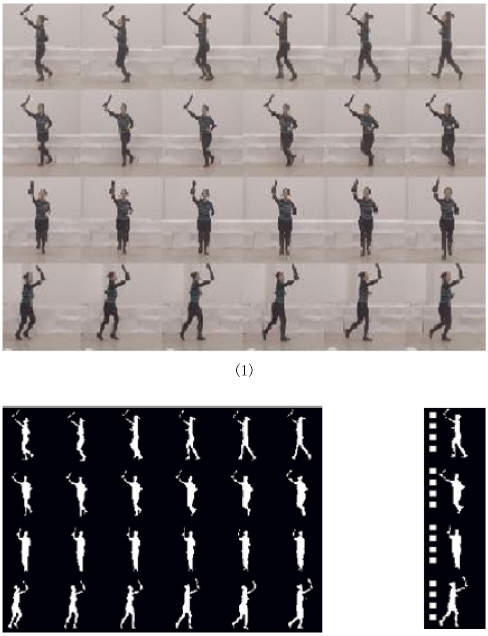
Let m_0 represent the minimum human physiological behavior understanding parameter, m_n represent the maximum human physiological behavior understanding parameter, and n represent the parameter tracking coefficient. With the support of the above physical quantities, the recognition result of parameter tracking behavior can be expressed by simultaneous formula (2)

$$C = H \cdot \sqrt{\frac{\sum_{m_0}^{m_n} (A_2 - A_1)^2}{f \times n^2}} \tag{3}$$

Among them, f represents the human physiological behavior understanding permission value based on complex network, A_1 and A_2 represent two different human physiological behavior index parameters respectively. So far, the calculation and processing of each coefficient application index have been completed. With the support of complex network theory, the method of human physiological behavior understanding and parameter tracking has been successfully applied.

4 Comparative Experimental Analysis

24 consecutive images are selected to form a behavior sequence, which is used as a sample to describe a behavior. The 24 consecutive images constitute a feature space, and the feature extraction from these 24 images is used as the input feature of behavior recognition. The continuous frame image is shown in Fig. 2. Figure 2 (1) shows a continuous action image of a behavior, Fig. 2 (2) is a corresponding binary image, and Fig. 2 (3) shows a continuous frame image of each corresponding behavior.



(1) (2) (3)

Fig. 2. Continuous frame image

Many pose recognition algorithms are characterized by a single binary silhouette image. But the behavior is composed of a continuous action sequence, so the STB index is used to determine the recognition accuracy of the change form of human physiological behavior. Generally, the larger the STB index value is, the higher the recognition accuracy of the complex network for the change form of human physiological behavior is, and vice versa. During the experiment, the experimental group was equipped with the method of human physiological behavior understanding and parameter tracking based on complex network theory, while the control group was equipped with the traditional multi-scale human physiological behavior analysis and understanding method.

According to the analysis of Table 2, with the extension of experimental time, the STB index of the experimental group kept rising, and the maximum value of the whole experimental process reached 88.8%. The STB index of the control group began to rise slightly and steadily after a period of time. The maximum value of the whole experiment was only 54.3%, which decreased by 34.5% compared with the maximum value of the experimental group. To sum up, after the application of human physiological behavior understanding and parameter tracking method based on complex network theory, the value of STB index shows a significant upward trend, which meets the practical application needs of enhancing the accuracy of complex network for human physiological behavior change recognition.

Table 2. Comparison of STB index values

Experiment time/(min)	STB index value/(%)	
	Experience group	Control group
5	81.6	40.2
10	82.1	40.2
15	82.4	43.1
20	82.7	43.1
25	82.9	45.8
30	83.2	45.8
35	83.8	48.3
40	84.0	48.3
45	84.3	48.9
50	84.5	49.4
55	84.7	49.8
60	84.9	50.3
65	85.3	50.9
70	85.8	51.4
75	86.2	51.8
80	86.8	52.3
85	87.4	52.8
90	87.8	53.4
95	88.3	53.7
100	88.8	54.3

5 Conclusion

Compared with the traditional multi-scale human physiological behavior analysis and understanding method, the human physiological behavior understanding and parameter tracking method based on complex network theory can model the human skeleton under the support of the centrality index of node association degree, and then combine the multi-scale feature extraction results to realize the accurate recognition of parameter tracking behavior. From the practical point of view, the increase of STB index value can enhance the recognition accuracy of complex network for human physiological behavior changes, and has strong practical application ability.

Fund Projects. The Doctoral Scientific Research Foundation of Liaoning Province (2019-BS-121), the Central Govermment Guided Local Special Funds for Scientific and Technological Development (2020JH6/10500067).

References

1. Zhang, Y.: Simulation design of human physiological parameters remote monitoring system based on single chip microcomputer system. J. Changchun Normal Univ. (Nat. Sci.) **39**(4), 28–31 (2020)
2. Yang, Z., Wang, W., Kim, D.: On multi-path routing for reliable communications in failure interdependent complex networks. J. Comb. Optim. **41**(1), 170–196 (2021)
3. Kadokawa, J.I., Tanaka, K., Yamamoto, K.: Enzymatic preparation of supramolecular networks composed of amylosic inclusion complexes with grafted guest polymers. J. Electrochem. Soc. **166**(9), B3171–B3175 (2019)
4. Xiong, K., Yu, J., Hu, C., et al.: Synchronization in finite/fixed time of fully complex-valued dynamical networks via nonseparation approach. J. Franklin Inst. **357**(1), 473–493 (2020)
5. Yang, Y., Pan, J., Zhou, Z., et al.: Complex microbial nitrogen-cycling networks in three distinct anammox-inoculated wastewater treatment systems. Water Res. **168**(1), 115142.1-115142.11 (2020)
6. Zhou, W., Li, B., Zhang, J.E.: Matrix measure approach for stability and synchronization of complex-valued neural networks with deviating argument. Math. Probl. Eng. **2020**(8), 1–16 (2020)
7. Fu, W., Liu, S., Srivastava, G.: Optimization of big data scheduling in social networks. Entropy **21**(9), 902 (2019)
8. Liu, S., Li, Z., Zhang, Y., et al.: Introduction of key problems in long-distance learning and training. Mob. Netw. Appl. **24**(1), 1–4 (2019)
9. Liu, S., Bai, W., Zeng, N., et al.: A fast fractal based compression for MRI images. IEEE Access **7**, 62412–62420 (2019)
10. Dai, H., Jia, J., Yan, L., et al.: Event-triggered exponential synchronization of complex dynamical networks with cooperatively directed spanning tree topology. Neurocomputing **330**(FEB.22), 355–368 (2019)